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A Binomial and Species-Independent Approach to Trap Capture Analysis of Flying Insects

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ABSTRACT Traps for monitoring of flying insect pests constitute a critical part of integrated pest management strategies. However, interpretation of trap captures is hampered by 1) factors associated with the performance of traps (i.e., lure, trap design, placement); 2) an often poorly defined relationship between trap captures and population density; and 3) interpretation approaches being highly specific to a certain insect species, trapping method, or trapping environment. The main purpose of this study was to identify a trap capture interpretation approach with little sensitivity to characteristics specific to a given data set, which would allow easier comparison of trapping data sets and make it easier to standardize sampling plans across insect pests and trapping environments. Based on fits of trapping data sets to standard distributions (normal, Poisson, and negative binomial), evaluations of the index of aggregation, *k*, and linear regression coefficients from Taylor's power law, we concluded that these characteristics varied considerably among data sets, which means that enumerative sampling plans may not be appropriate. Across 13 trapping data sets of six insect species, we showed a consistent nonlinear relationship between average trap captures and number of traps with zero captures and that the *k* can be stabilized by converting trapping data into binomial data. A trap interpretation approach based on number of zero captures is both easy to use, was found to be species-independent, and means that it may be possible to establish meaningful and reliable action thresholds based on trap captures of flying insects. Although developed using trapping data from food facilities, this approach may have application to trapping data from other environments as well.

KEY WORDS IPM, monitoring, sequential sampling, binomial data

Effective integrated pest management (IPM) strategies rely heavily on early and accurate detection of emerging pest populations. Thus, monitoring of insect pests populations, based on trap captures, constitutes a critical component of IPM and has been the main focus of many ecological studies during the last four decades. Many studies underscore the usefulness of monitoring programs, based on trapping of flying insects, in early detection and as decision support tool (based on action thresholds). However, the usefulness of monitoring data in IPM programs seems to be frequently hampered by an inconsistent and often poor relationship between trap captures and actual insect population densities (Vela-Coiffier et al. 1997, Hagstrum et al. 1998, Nansen et al. 2004a, Toews et al. 2005), which raises the fundamental question about what a given set of trap captures actually means? Another challenge is that interpretation of trap captures tend to work well for some data sets but not for others. For example, Nansen et al. (2001) developed a fairly robust weather-driven regression model of weekly *Prostephanus truncatus* (Horn) (Coleoptera: Bostrichidae) flight activity for southern Benin. Based on independent validation data, the authors showed that 1) *P. truncatus* flight activity was predicted well elsewhere in southern Benin, 2) in central Benin new coefficients for the same environmental variables were needed to produce an adequate prediction, and 3) the model did not fit pheromone baited trap catches from northern Benin. Such inconsistency in the accuracy of interpretation approaches is obviously associated with a wide range of environmental and physiological factors, but it also is associated with many factors associated with the actual performance of traps, including trap type (Levinson and Hoppe 1983; Ahmad 1987; Barak et al. 1990; Mullen 1992; Quartey and Coaker 1992; Hussain et al. 1994; Mullen et al. 1998; Mullen and Dowdy 2001; Nansen et al. 2003, 2004b), visual cues on traps (Quartey and Coaker

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Table 1. Trap captures of *P. interpunctella* with water bottles in two peanut warehouses were analyzed for their fit to three standard distributions: normal, Poisson, and negative binomial

Warehouse	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11
Warehouse 1											
Total captures	24	44	54	66	102	148	250	486	631	857	933
Zero captures	23	17	14	13	12	8	4	3	1	1	0
Normal	S	S	NS	NS	NS	S	S	S	NS	S	S
Poisson	S	S	NS	S	S	S	S	S	S	S	S
Negative binomial	NS	NS	NS	NS	NS	NS	S	S	S	S	S
Warehouse 2											
Total captures	21	72	100	197	290	389	676	962	1084	726	
Zero captures	25	10	10	10	4	2	0	0	0	0	
Normal	S	S	NS	NS	NS	S	S	S	NS	S	
Poisson	S	S	NS	S	S	S	S	S	S	S	
Negative binomial	NS	NS	S	NS	NS	NS	S	S	S	NS	

S denotes that the observed weekly data set was significantly different ($P < 0.05$) from expected (predicted based on standard distribution); NS denotes no significant difference between observed and predicted.

1992), pheromone composition (Phelan and Baker 1986, Zhu et al. 1999), pheromone dosage in lures (Vick et al. 1986, Hussain et al. 1994, Nansen et al. 2006b), air movement (Quartey and Coaker 1992), and trap placement (Vick et al. 1986; Nansen et al. 2003, 2004c).

When analyzing trap captures, variation in accuracy of interpretation approaches is a problem, because it adds serious constraints to the usefulness of a given analysis, makes it very difficult to compare interpretations of different data sets, and it also hampers attempts to standardize sampling protocols for different insects and/or across ranges of trapping environments. It would therefore be desirable if it was possible to identify an interpretation approach that would be less sensitive to insect species, trapping method and environment. We suspect that use/interpretation of trap captures in IPM programs is hampered, because we are mainly focusing on establishing direct links between absolute counts of insect in traps and their occurrence within the given sampling space and focus on 1) how well trapping data and/or combinations of environmental variables (i.e., weather conditions) can be used to predict/forecast insect pest populations over time and space and 2) how to develop action thresholds based on trapping data. Much less attention has been given to the frequency distribution of trap captures and to what extent changes in frequency distribution may reflect changes in population densities. The most simple approach to analysis of trap capture distribution is to examine the binomial distribution of captures (presence/absence). That is, the purpose of such an analytical approach would not be to locate/identify hot spots with high infestation levels nor to predict the pest population in weeks ahead, instead the objective could be to use the proportion of zero captures (empty traps) as an indicator of whether current monitoring data indicate a need for treatment (or any other kind of action).

In this study, we evaluated different standard interpretation methods related to sequential sampling, and the main purpose is to identify an approach that can be used across a wide range of species (is species in-dependent) and trapping environments. We examined fits of trapping data to standard distributions (normal, Poisson, and negative binomial), the index of aggregation, *k*, and regression coefficients from Taylor's power law (TPL), and evaluated Sequential Probability Ratio Test (SPRT) and Iwao confidence interval sampling plans. In addition, we investigated the relationship between zero captures and total insects captured in 13 trapping data sets of six insect species and developed a modified sequential sampling plan based on binomial data (proportion of traps with zero insects captured). This analysis is used to discuss common features in trap data sets and improved interpretation of trap captures in general. Although this study is based on trapping data from food facilities, a similar interpretation approach may be applied for monitoring pest status in field crops, forests, greenhouses, and urban environments.

Materials and Methods

Trapping Data from Food Processing Facility, 1993–1996. Trap captures of the almond moth, *Ephestia cautella* (Walker) (Lepidoptera: Pyralidae), were obtained from the ground floor of a 70- by 70-m food processing facility. A monitoring grid with 130 traps was established in November 1993, and trapping was completed 21 March 1996. Traps were serviced in 10–35-d intervals for a total of 51 trapping events, with 6,519 individual trap captures (Table 1). In two of these trapping events, only 70 and 107 traps were serviced, whereas in the remaining trapping events less than two traps of 130 were missing. There was considerable variation in age of lures and traps (7–112 d) and in the length of service intervals, but within trapping events all traps contained lures with same ages. Also, these results are typical for commercial settings, which are the intended environment for the proposed sampling plan.

Trapping Data from Peanut Warehouses, 2007. Trapping data of the Indianmeal moth, *Plodia interpunctella* (Hübner) (Lepidoptera: Pyralidae), were collected from two peanut warehouses in northwestern Texas (Table 1). For monitoring, we used 250-ml water bottles filled with ≈150 ml of tap water, and two diagonal rectangles (4 cm in width by 2 cm in height) were cut in each bottle, and the "lip" was folded outward to serve as a landing platform. Peanut warehouse 1 was 40 m in width, 200 m in length, and 60 m in height at the tallest point and had a sloped roof. The total capacity was 10,000 tons of unshelled peanuts (runner type), and monitoring was conducted in a one-fourth section of the warehouse, which was fully loaded so that the headspace above the peanut pile was ≈1–1.5 m. In total, 36 traps were placed in 3-m intervals with outer traps ≈1–2 m from side walls. Trapping was initiated 23 April, 2007, and all traps were serviced weekly for 11 consecutive weeks. Trapping was terminated when the warehouse was fumigated with phosphine 13 July. The peanut warehouse 2 was 40 m in width, 100 m in length, and 40 m in height with a flat roof. The total capacity was 10,000 tons of unshelled peanuts (runner type), and trapping was conducted in a one-fifth section of the warehouse. The peanut pile was flat (horizontal) all across the top of the sampling area and ≈20 m in height, and there was 3–4-m headspace. Horizontal ropes were attached to side walls and vertical wires and sampling devices were suspended from these ropes in an asymmetric grid pattern in 3-m intervals. In warehouse 2, we initiated the trapping program 14 May and continued for 10 consecutive weeks, and which point the peanuts were processed and shelled.

Additional Data Sets. Nansen et al. (2003) analyzed pheromone-baited trap captures of the warehouse beetle, *Trogoderma variabile* Ballion (Coleoptera: Dermestidae) with two different trap types: Pherocon II (Trécé, Adair, OK) and FLITe-TRAK beetle trap (Mullen 1992) (Table 1). In both trap types, a rubber septum impregnated with synthetic sex pheromone of *T. variabile* was used as attractant and trapping was conducted for nine weeks ($N = 18$). Trapping data described in Nansen et al. (2004a) included captures of foreign grain beetle [*Ahasverus advena* (Waltl) (Coleoptera: Silvanidae)], red flour beetle [*Tribolium castaneum* (Herbst.) (Coleoptera: Tenebrionidae)], maize weevil [*Sitophilus zeamais* Motschulsky (Coleoptera: Curculionidae)], and *P. interpunctella.* These insects were captured weekly with unbaited sticky traps at 20 trapping locations over 16 consecutive weeks.

SPRT Sampling Plan. Each of the 21 weekly trap capture data sets of *P. interpunctella* with water bottles in peanut warehouses were compared with those predicted from the following standard frequency distributions using formulas available in Excel (Microsoft, Redmond, WA): normal, Poisson, and negative binomial (NB). Differences between observed and predicted were analyzed with a chi-square test. Regarding predictions based on NB distributions, k parameters were calculated for each weekly data set. The k parameter, an index of aggregation, is a positive number calculated when fitting data to positive binomial and/or NB distributions. The standard formula for calculation of the k of data following an NB distribution (where mean < variance) is $k = \text{mean}^2/(\text{variety-mean})$ (Pedigo and Zeiss 1996). However, if data follow a positive binomial distribution (mean [m_t] variance), the same formula is modified to: $k = \text{mean}^2/(\text{mean-variety})$ (Pedigo and Zeiss 1996). In the positive binomial distribution, the k is used to calculate p, the probability of trapping an insect, such that $p = \text{mean}/k$, and it is clear that $k \geq 0$. Initially, fitting trap captures of *P. interpunctella* to a positive binomial distribution was therefore not considered relevant as the mean:variance of absolute counts was <1, which resulted in negative k estimates.

To examine the importance of varying k in development of sampling plans, Wald's SPRT sampling plan for an NB distribution (Binns 1994) was developed for trap captures of *P. interpunctella* with water bottles in peanut warehouses. Three pieces of information are needed for the development of SPRT sampling plans: 1) a known or assumed frequency distribution, 2) the economic threshold, and 3) acceptable level of risk associated with action threshold estimates (Pedigo and Zeiss 1996). In an SPRT plan, m_0 represents the upper threshold for a low population density that does not require action, whereas m_1 represents the lowest population density at which action is recommended (Pedigo and Zeiss 1996). The critical threshold, m_t, is defined, "below which [treatment] is not desirable and above which it is desirable" (Binns 1994). The m_t is considered the midpoint of a probability interval between 0 (no action is taken) and 1 (action is taken) as a function of insect counts. That is, when insect counts are either very low or high, the sampling plan can with high accuracy determine that no action or action is needed, but the operating characteristic (OC) is used to describe this relationship, around m_t, when insect counts are within an intermediate range. Generally, the steepness of the slope of OC within an intermediate range indicates the robustness of a sampling plan (Binns 1994). A shallow slope of OC around m_t indicates a higher probability of error. The risks of type 1 and type 2 errors are determined by user-defined levels of α and β, respectively, and they are typically set at either 1 or 5%. The sampling plan approach is also used to characterize the relationship between insect counts and estimated average sample number (ASN) required to determine whether action is needed or not. The ASN is expected to reach peak values at and around m_t. To determine OC and ASN, we used a C++ program (Meikle et al. 2000) to rerandomize the order in which trap captures were examined within each trapping event (1,000 iterations) from both peanut warehouses and apply sampling plans to each rerandomized set. Each iteration repeated the sequential sampling procedure using the trapping data, changing only the order in which trap captures were drawn.

Taylor's Power Law and the Iwao Confidence Interval Sampling Plan. Taylors power law (Taylor 1961) is used in development of Iwao (distribution-free), enumerative sequential sampling stop lines and was considered here as an alternative approach to SPRT plans. We determined linear regression coefficients, a (slope) and b (intercept) after applying Taylor's power law to each of the 13 data sets of *P. inter-*

punctella in peanut warehouses, and coefficients from each data set were compared statistically with those from the linear regression coefficients based on all 189 data points combined. Thus, we tested whether the individual data sets were statistically different from the overall mean. Pairwise statistical comparisons of linear regression coefficients from one data set with those from all data points were conducted based on Wiley et al. (1998), and each coefficient, *a* and *b*, were examined separately. In brief, parameter estimates were examined based on a *t*-test and the following equations:

$$t = \frac{(x_1 - x_2)}{\sqrt{(x_{se\,1}{}^2 + x_{se\,2}{}^2)}} \qquad [1]$$

where x_1 is the parameter estimate of either *a* or *b* from one of the 13 data sets, x_2 is the parameter estimate of either *a* or *b* based on all data points, and x_{se} is the standard error associated with each parameter estimate. And degrees of freedom (*df*) of the *t*-test were as follows:

$$df = (n_1 - 2) + (189 - 2 = 187) \qquad [2]$$

In which n_1 is the number of observations in a given data set and 187 is equal to the number of all observations minus 2.

Parameters from the TPL analysis were used to construct sampling stop lines by using the Iwao confidence interval method (Binns 1994) for the same data set used in the SPRT plan described above. Parameters needed for the Iwao plan include the TPL parameters, *a* and *b*, as well as the midpoint between mt and z_{α}, where z_{α} is the $100(1 - z_{\alpha})\%$ normal deviate. In our analysis, $z_{\alpha} = 1.96$. As with the SPRT analysis, 1,000 rerandomized interations of each sampling occasion were conducted.

Relationship between Total Captures and Number of Zero Captures. We examined the relationship between total captures and proportion of zero captures for each trapping event in each of the 13 data sets. Only trapping events with at least one insect captured are included (Table 1), and we conducted a regression analysis of proportion of traps with zero captures $F(x)$ as a function of average trap captures (equation 1):

$$F(x) = i \times \exp^{-j \times x} \qquad [3]$$

In which *i* and *j* are fitted coefficients, and *x* is the average trap capture. This curve fit was chosen because it is simple and initial analyses provided high level of predictive accuracy. The estimated coefficients, *i* and *j*, from each of the 13 data sets were examined in the same way as we examined coefficient estimates of *a* and *b* from linear regression fits to Taylor's power law (equations 1 and 2).

Binomial Sequential Sampling Plan. Observed trap captures from all 13 data sets were converted into binomial data (presence, 1 and absence, 0), which resulted in a mean:variance ratio >1, so it was considered appropriate to fit each data set to a positive binomial distribution. One considerable advantage of using data sets that follow a positive binomial distribution is that the calculation of the decision lines, d_0 and d_1, becomes independent of the *k* (Pedigo and Zeiss 1996). In the binomial sampling plan presented here, m_1 and m_0 denote proportional thresholds, with m_0 being the highest proportion of traps with trap captures that does not require action, whereas m_1 represents the minimum proportion of traps with trap captures at which action is recommended. For example, $m_0 = 0.4$ means that action is not required when <40% of traps contain insects, and $m_1 = 0.7$ means that action should be taken when >70% of traps contain insects. For such action thresholds to be meaningful to a specific pest problem, they would have to be based on an economic analysis of economic injury level (Pedigo 1994), which was beyond the scope of this study.

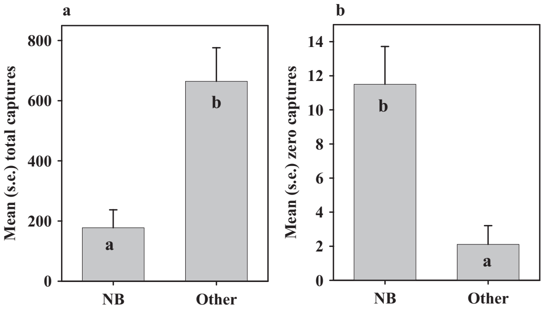

Fig. 1. Relationship between fit/nonfit of weekly trap captures of *P. interpunctella* with an NB distribution and average trap captures (a) or average number of zero captures (empty traps) (b). NB denotes weekly that sets that were nonsignificantly different from an NB; Other denotes weekly that sets that were significantly different from an NB. Letters represent significant difference at the 0.05 level.

Results

Evaluation of Sampling Plans. One of the first steps in development of sequential sampling plans is determining how well a given data set fits standard frequency distributions. We found that trap captures of *P. interpunctella* in peanut warehouses: 1) fit a Poisson distribution for only 1 wk in each warehouse (two of 21 weekly data sets), 2) fit a normal distribution in four weekly data sets from each warehouse; and 3) fit a NB distribution in six weekly data sets from each warehouse (12 of 21 data sets) (Table 1). With the NB distribution providing the most consistent fit to weekly trapping data, differences between weeks with significant and nonsignificant fits was examined, and a significant fit to NB distribution was significantly associated with low total trap captures ($F = 16.92$; df = 1, 19; $P < 0.001$) and/or high number of trapping locations with zero captures ($F = 11.71$; df = 1, 19; $P = 0.003$) (Fig. 1). Despite fairly consistent fit of the 21 weekly data sets to a NB distribution, estimates of *k* showed marked variation (average, 2.72 ± 0.51, min., 0.47; max, 9.00) and were significantly correlated with mean trap captures ($R^2 = 0.62$; $F = 30.52$, df = 1, 20; $P < 0.01$). To illustrate the importance of *k* estimates varying close to 20-fold, we examined two scenarios

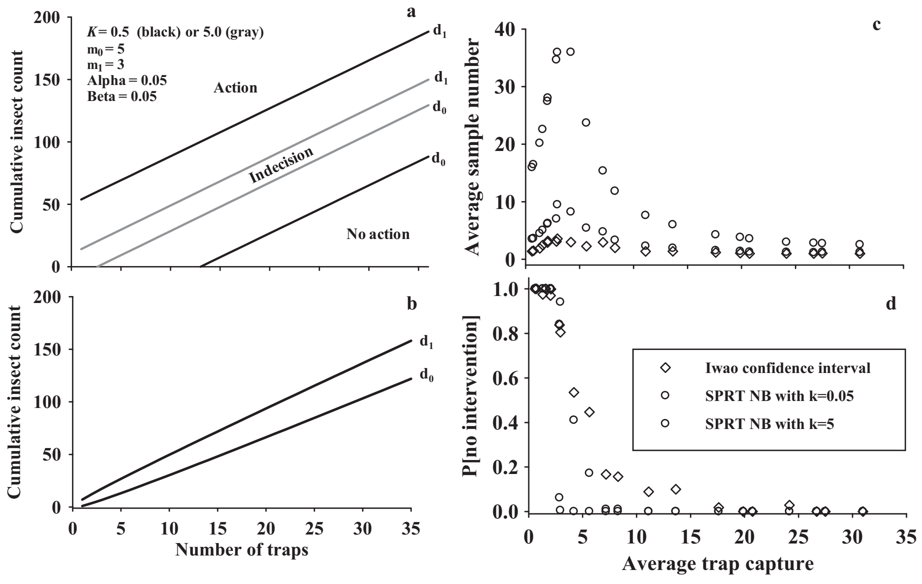

Fig. 2. Trap captures of *P. interpunctella* with water bottles ($N = 21$) were used to develop an Iwao sampling plan and SPRT sampling plans for two scenarios with equal d_0 and d_1 values and α and β values but different k: 0.5 and 5.0. Stop lines of SPRT (a) and Iwao (b) sampling plans, average sampling number (c), and the risk of type 1 error ($m > m_t$) (d).

within the observed trap capture range and $k = 0.5$ and 5.0 and with cumulative action thresholds, m_0 and m_1, of 3 and 5. A low k (high level of aggregation) generally increased the required sampling effort and the distance between the stop lines (Fig. 2a). Thus, $k = 0.5$ would in this case mean that at least 13 traps would have to be serviced to determine that action would not be necessary. However, if $k = 5.0$, then the minimum sampling effort was reduced to less than three traps and the distance between the stop lines likewise reduced. The ASN (Fig. 2c) differed considerably between the two sets of stop lines, because only a maximum of ≈10 traps on average were needed to make a decision when $k = 5.0$, whereas if $k = 0.5$ all available traps were not sufficient for a decision when density was between m_0 and m_1. Results from the iterative analysis showed that the OC differed somewhat between the two sets of stop lines (Fig. 2d) and that the risk of an error was high when the average trap capture per trap was <5. A highly variable, density-dependent or species-specific k is therefore a considerable problem when developing sequential sampling plan to be used in a wide range of trapping environments and within a considerable range of trap captures. Due to the highly variable estimates of k, an Iwao (distribution-free) sampling plan based on Taylor's power law coefficients also was conducted (Fig. 2b). The distance between the Iwao stop lines was considerably less than those for either SPRT plan. A narrow "no decision" zone leads to fast decisions, as was observed with the low ASN across all densities: the ASN was less than four across all observed densities. Although this has the advantage of providing a rapid answer to someone using the plan, the error rate was also very high, indicating that the results could not be considered in any way accurate. As seen in the OC data, even when the known trap density was ≈8 insects per trap, 16% of the sampling runs indicated a "low" density (less than three insects per trap).

As part of our evaluation of sequential sampling plan approaches, Taylor's power law was used to examine 13 trapping data sets of six different insect pest species (*P. interpunctella*, *E. cautella*, *T. variabile*, *A. advena*, *L. minutus*, and *T. castaneum*) captured with both baited and unbaited traps. Our analysis revealed that seven of the 13 estimates of regression coefficient a (slope) and five regression coefficient of b (intercept) were significantly different from the same estimate of all data points. In 10 of the 13 data sets at least one of the regression coefficients, a and b, was significantly different from those of all data sets combined.

Relationship between Total Captures and Number of Zero Captures. Even though nine of 21 weekly trapping data sets of *P. interpunctella* in peanut warehouses were significantly different from a NB distribution, close examination of predictions derived from the NB distribution showed that number of trapping locations with zero captures was predicted accurately for all data sets ($R^2 = 0.965$; $F = 531.2$; df = 1, 20; $P < 0.001$). Thus, we pursued this approach further by fitting all trapping data sets combined to the NB distribution and showed that number of trapping locations with zero captures could be predicted accurately ($R^2 = 0.978$; $F = 7804.8$; df = 1, 189; $P < 0.001$) (Fig. 3). That is, the entire range of a trapping data set may not show a good fit to the NB distribution, but predictions of zero captures were very accurate. We also showed that there was a highly significant correlation between proportion of zero captures and average trap capture ($R^2 = 0.53$, $a = 0.86$, $b = 0.39$; $F = 219.9$; df =

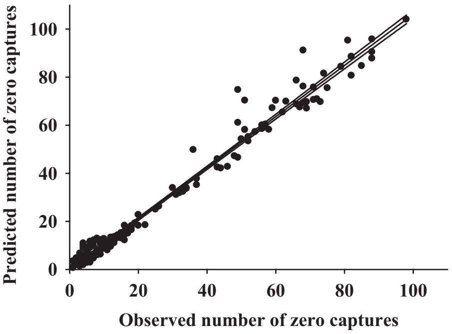

Fig. 3. Using all trap captures (Table 1), we examined the relationship between observed and predicted number of zero captures based on a fit of weekly data to a negative binomial distribution. A linear regression was conducted and is presented together with 95% confidence intervals.

1, 189; $P < 0.001$) (Fig. 4). Based on equation 2, we found that in three of the 13 estimates of regression coefficient i was significantly different from the same estimate of that from all data points, and five of the 13 estimates of regression coefficient j were significantly different from the same estimate of all data points (Table 2). Thus, regression coefficients based on equation 2 were slightly more robust (similar to overall means) compared with those derived from Taylor's power law and suggested that there may be a fairly consistent relationship between average captures and zero captures across in data sets of a wide range of flying insect species. The regression line in Fig. 4 suggested that with average trap captures of five individuals, ≈80% of the traps contained insects and that a further increase in trap captures dramatically decreased the proportion of traps with zero captures.

Binomial Sequential Sampling Plan. Due to the strong correlation between observed and predicted number of zero captures (Fig. 3) and the consistent and highly significant relationship between the number of zero captures and average trap captures (Fig. 4), a binomial sequential sampling plan (presence/absence) was examined on the basis of all 13 data sets. Transformation to binomial data resulted in a mean: variance ratio >1, so all data sets were fitted to a positive binomial distribution, and consistent k estimates were obtained from all data sets (Fig. 5). Standard errors associated with each mean k estimate were <0.1, and the maximum k was only 2–3 times the mean (compared with 20-fold range when k estimates were based on fit to NB distribution). Such consistent k estimates are noteworthy as both total trap captures and numbers of traps used varied considerably among data sets. Because the mean:variance ratio >1 for the binomial data, a positive binomial distribution was assumed to provide the best fit. When data are considered to follow a positive binomial distribution, the decision lines in a sequential sampling plan are independent of the k, because they are exclusively determined by m_0, m_1, and levels of acceptable risk (α and β). The risk of a type I error, α, and that of a type II error, β, associated with the d_0 and d_1 stop lines were each set to 1 and 5%. In an SPRT sampling plan, the stop lines are parallel, because decisions are based on cumulative counts. But in the analytical approach presented here, we used proportional data (proportion of traps with or without captures), so the y-axis ranged from 0 to 1. This transformation was obtained by dividing estimates of d_0 and d_1 with the number of trapping stations. Using the settings outlined above ($m_0 = 0.4$, $m_1 = 0.7$, α and $\beta = 0.01$) and assuming fit to a positive binomial distribution, formulae available in Pedigo and Zeiss (1996) shows that, for instance, 20 trapping stations provide estimates of d_0 and d_1 equal to 7.4 and 14.7, respectively. We divided these estimates with 20 and thereby obtained proportional estimates of d_0 and d_1 equal to 0.4 and 0.7 for 20 trapping stations. Due to this proportional transformation, the stop lines were asymptotic approaching 0.55. According to the curve in Fig. 4, there was a large increase in average trap captures when the proportion of zero captures fell below 0.40. For this reason, 0.7 was proposed as m_1 and 0.4 as m_0. Figure 6 shows proportional stop lines based on a positive binomial distribution,

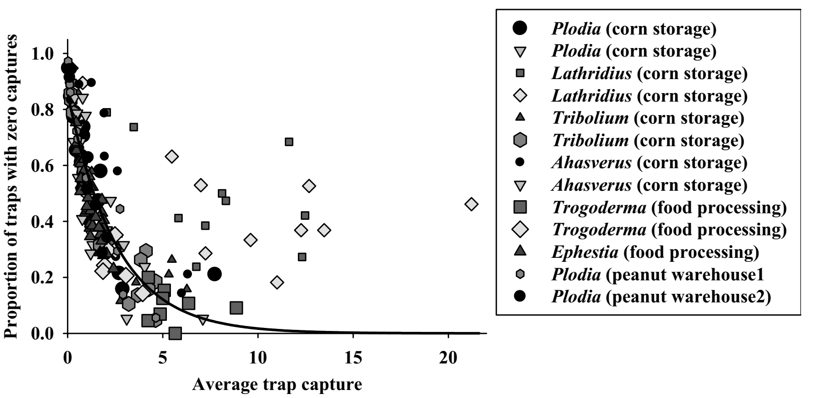

Fig. 4. Thirteen data sets (Table 1) were examined for the relationship between average trap capture and proportion of zero captures. The decaying curve fit (equation 1 represents the regression of all data combined, whereas statistics for each of the data sets separately are presented in Table 1.

Table 2. Data sets included in analysis of relationship between average captures and number of zero captures

Genus	Trap	Lure	Wk	Ht	No.	Avg (min.-max)	R^2	F	i	j	Reference[a]
Trogoderma (2)	Flite-Trak	P	9	a	35	5.18 (2.32–8.86)	0.51	9.22*	0.78	0.36	a
Trogoderma (2)	Pherocon II	P	9	b	35	2.25 (0.86–3.94)	0.63	14.4**	0.62	0.33	a
Plodia (1)	Pherocon II	N	15	a	20	1.47 (0.05–7.74)	0.78	55.0***	0.95	0.68	b
Tribolium (4)	Pherocon II	N	14	a	20	2.61 (0.17–6.26)	0.94	217.3***	0.93	0.51	b
Lathridius (7)	Pherocon II	N	12	a	20	6.55 (0.14–12.47)	0.88	72.0***	0.98	0.19	b
Ahasverus (5)	Pherocon II	N	10	a	20	2.35 (0.11–6.32)	0.96	252.5***	1.00	0.35	b
Plodia (1)	Pherocon II	N	16	b	20	0.97 (0.23–3.11)	0.87	97.0***	0.93	0.42	b
Tribolium (4)	Pherocon II	N	14	b	20	2.39 (0.14–4.63)	0.89	126.5***	0.95	0.41	b
Lathridius (7)	Pherocon II	N	11	b	20	9.21 (0.21–21.62)	0.56	13.6**	0.89	0.07	b
Ahasverus (5)	Pherocon II	N	10	b	20	2.03 (0.11–7.11)	0.53	13.5**	0.86	0.08	b
Ephestia (6)	Pherocon II	P	51	a	130	1.16 (0.45–2.42)	0.76	165.0***	0.83	0.50	
Plodia (2)	Bottle	W	11	a	36	1.39 (0.03–4.64)	0.96	224.7***	0.70	0.28	
Plodia (2)	Bottle	W	9	a	35	0.90 (0.09–2.09)	0.9	85.8***	0.73	0.26	

Trapping data of six insect species were collected from different food facilities using different trapping devices (trap) and lures (P, pheromone; N, unbaited; and W, water). In several of the food facilities, trapping data were collected at two heights (a, high; and b, low) within the same facility. No. denotes the number of traps deployed in each data set, and Avg (min.-max) denotes average, minimum, and maximum captures, respectively. R^2, F, a, and b are results from regression analyses of the data shown in Fig. 1. *$P < 0.05$, **$P < 0.01$, and ***$P < 0.001$. Numbers in parentheses after genus names denote column number in Fig. 5.

[a] a, Nansen et al. (2003) and b, Nansen et al. (2004).

and it is seen that 1) <10 trapping stations are used, it is not possible to accurately determine whether action is needed or not; 2) with 20 trapping stations, ≈70% of traps containing insects would merit action and <40% of traps containing insects would suggest that no action is needed; and 3) although both stop lines asymptotically approach 0.55, it is seen that the two lines become close to parallel if >35 trapping stations are used, which may be used as an indicator of maximum number of trapping stations.

Discussion

Successful implementation of IPM strategies largely depends on the development of cost-effective, user-friendly, and reliable monitoring programs. However, most attempts to develop direct associations between trap captures and population densities have, at best, been inconsistent, and a wide range of studies have highlighted factors (e.g., trap type, lure, trap placement) that hamper interpretation of trapping data sets. In this study, we showed that 1) the k associated with trap captures showed considerable variation, and we demonstrated how a varying k causes complications when developing SPRT sampling plans, 2) number of traps with zero captures could be predicted very accurately when trap captures were fitted to the NB distribution, 3) linear regression coefficients from fits to Taylor's power law were modestly consistent but not as consistent as those from an exponentially declining fit to the relationship between average captures and number of zero captures, and 4) conversion of trap captures into binomial data provided the framework needed to modify interpretation of trapping data in a way that was species- and k-independent.

Considerable research effort has been invested in developing trap-capture based IPM, but the nature of operations in food facilities (sanitation, turnover of food products) seems to hamper development of IPM tools for accurate short- and long-term predictions of

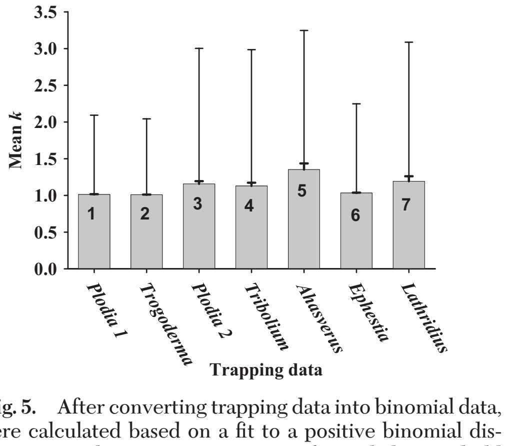

Fig. 5. After converting trapping data into binomial data, k were calculated based on a fit to a positive binomial distribution. Gray bars represent averages for each data set, bold error bars denote SE, and thin error bars denote maximum. The seven bars represent trapping data in Table 1, in which numbers in brackets after genus names refer to the bars in this figure.

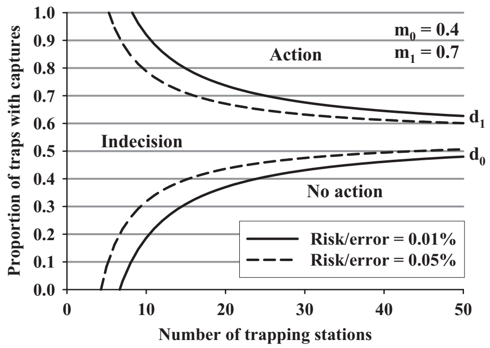

Fig. 6. Proportional stop lines based on binomial data with an assumed fit to a positive binomial distribution, which means that the decision lines are independent of the k.

insect pest densities over time. In stored grain environments, numerous studies have investigated the association of abiotic conditions with fluctuations in trap captures of flying insect, but use of abiotic variables in forecasting is limited by the difficulty in predicting weather accurately more than a few days ahead. Spatial prediction of insect infestations in stored product environments is based upon knowledge about the spatial structure of the given data set, and semivariogram analysis is a well-known initial approach to examine the spatial structure analysis (Isaaks and Srivastava 1989, Liebhold et al. 1993, Brenner et al. 1998). Semivariogram analyses of insect counts acquired from stored food and food processing facilities often show random spatial patterns (Nansen et al. 2003), and a random spatial data structure means that it is not possible to predict insect counts at unsampled locations, which again means that contour mapping and other continuous spatial tools cannot be recommended (Nansen et al. 2006a). Thus, both temporal and spatial predictions of trap captures have faced considerable challenges and made it somewhat difficult to determine exactly what a given trap catch actually means. The basic root to both of these challenges is a poor and inconsistent relationship between trap captures and actual population densities. An alternative to both temporal and spatial prediction of absolute trap captures is to focus on the frequency distribution of trap captures.

Our comparison of SPRT and Iwao (distribution-free) sampling plans showed that the level of in-decision (distance between stop lines) was less in the Iwao sampling plan, but this sampling plan approach also was found to have the highest level of error. A low ASN is not necessarily a fixed characteristic of Iwao confidence interval plans; Binns (1994) and Meikle et al. (1998) found that the Iwao method resulted in ASN values several times higher, when insect densities were between stop lines, than those observed with SPRT plans constructed using the same data. These varying results indicate that the Iwao method may be a better approach than the SPRT, but it seems to be quite sensitive to the stop line parameters and estimates of the TPL parameters. Regarding stored grain insects, sequential sampling plans have been developed for direct sampling, for example insects per maize, *Zea mays* L., ear or volume of grain (Subramanyam et al. 1997, Meikle et al. 2000, Toews et al. 2002), but few studies have been published on the development of sequential sampling plans for trapping data of flying insects in stored product environments. Carvalho et al. (2006) trapped cigarette beetles, *Lasioderma serricorne* (F.) (Coleoptera: Anobiidae) at 26 pheromone-baited locations. With upper and lower action threshold of three and five beetles per trap per wk, $k = 1.09$, and 5% error associated with action threshold estimates, the authors concluded that six to seven trapping stations would be a sufficient for determining whether action is required (this conclusion was based on the intercept of d_0 with the x-axis). One of the main assumptions behind an SPRT sampling is that the k is constant (Bliss 1958). However, this is not always the case (Southwood 1978, Elliott 1983), and we found k to vary ≈20-fold among 21 weekly data sets and that the mean number of samples required to make an accurate decision ranged from between 10–40 (Fig. 2b). Thus, changes in k can considerably affect sequential sampling plans that assume data to follow a NB distribution. Figure 3 in Carvalho et al. (2006) showed ASN to vary between three and 27, with highest number of required insect counts at three beetles per trap per wk. Thus, although the Carvalho et al. (2006) concluded that six to seven trapping stations would be a sufficient, their data seemed to corroborate our analysis—that the accuracy of sequential sampling plans and number of required insect counts are highly influenced by trap capture densities. ASN curves varying as much as between three and 27 is less of a practical problem, when sequential sampling plants are based on insect counts from entire plants, soil samples, or leaves, because one can easily vary the number of samples collected in each sampling event. However, monitoring of insect populations based traps means that the user/researcher has already established a predetermined number of trapping stations, and, for a given trapping period, one would not suggest only to service three of 27 traps; once installed, all traps are typically serviced for each trapping period. Also, these sampling plans assume that sample units are collected at random from the sampling universe. If, for example, 25 traps are placed in a warehouse, then these would have to be serviced in a random order and that all insects are counted in each selected trap, if the objective was to interpret trapping data with a sequential sampling plan.

The clear correlation between average trap captures and number of zero trap captures suggests a modified sampling approach, in which the emphasis is on the number of empty traps. We showed that conversion into binomial data stabilized k estimates across a wide range of trap capture densities and across multiple species. Based on Fig. 6, we propose that between ≈25 trapping stations should be used in monitoring programs, because 1) a lower number of traps is associated with considerable in-decision (distance between stop lines), and 2) little additional robustness is obtained when >25 traps are used. Although based on completely different assumptions and requirements related to spatial statistics, Nansen et al. (2003, 2006a) suggested a similar recommendation of 25–35 trapping stations within a given sampling space. It was beyond the scope of this study to develop a sequential sampling plan for trap catches, as that would require determination of economic thresholds, which are likely to be species-specific and vary among food facilities. Instead, the main purpose was to propose a novel approach to interpreting of trap captures which is independent of the k and seemed to be consistent across a very wide range of insect pest species, trapping environments and types of monitoring devices. Using a trap capture interpretation approach that is more consistent across insect densities and species and across a wide range of trapping environments enables development of more consistent sampling plans and more consistent comparison of data sets.

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